Three Dimensional Modeling and Dimension Estimation of Indoor Scene

Synopsis of the PhD Thesis

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1. Abstract

The application of 3D point cloud data has gained significant traction in the field of advanced building and manufacturing. This paper presents a comprehensive methodology for refining line frame construction from indoor 3D point clouds directly. The proposed methodology integrates edge detection methods, and Alpha Shape computation to achieve an accurate representation of indoor structural geometry. The usefulness and robustness of the methods have been demonstrated by extensive analyses of several scenarios of indoor scene environments. The study evaluates this methodology across three distinct datasets, denoted as Cases A, B, and C, each representing varying degrees of indoor room complexity. The edge identification approach uses PCA-based geometric descriptors in conjunction with DBSCAN clustering to accurately locate and segment edge points, resulting in the creation of full wireframe models. The utilization of the Rolling Ball Pivoting algorithm in the computation of the Alpha Shape facilitates the enhancement of the wireframe structure, hence enabling accurate representation. The methodology excels at accurately representing structural boundaries, door apertures, and windows, outperforming existing unsupervised methods with an outstanding Intersection over Union (IoU) of 0.9 and a remarkably low Error Rate (ER) of 0.081 compared to the Voxel Clustering method. While proficient in capturing complex scenes, the study acknowledges limitations, suggesting potential areas for refinement. The findings underscore the efficiency and adaptability of the proposed algorithm, offering valuable insights for future enhancements and diverse applications.

2. Introduction

In recent years, the rapid advancement in sensor technology has propelled the swift development of Light Detection and Ranging (LiDAR) technology. The widespread availability of 3D laser scanning equipment has led to an unprecedented surge in 3D point cloud data, often comprising tens of millions of samples. However, the inherent unstructured, irregular, and non-uniform nature of raw point cloud data has underscored the imperative for concise and meaningful abstractions. Among these, 3D line segment structures emerge as pivotal features for human perception, finding application in diverse domains such as building outline extraction [1], building model reconstruction [2,3], road extraction [4], registration [5], localization [6], calibration [7] and so on.

While the detection of line segments from 2D images has been extensively studied [8-12], the exploration of 3D line segment extraction remains insufficient. Notably, unorganized point clouds lack connectivity information, posing challenges in detecting 3D line segments within vast and heterogeneous datasets. Many existing approaches have faltered when confronted with the demand for fast and accurate 3D line segment extraction from large-scale building point clouds. This is attributed, in part, to the difficulty in formalizing the definition of a "line segment" due to the diverse and complex real-world scenes. Perceptible line segments are influenced by factors such as sudden changes in curvature or color, sharp edges, and plane intersections.

Existing 3D line segment extraction methods [13] often follow a two-step process: (1) conversion of the input point cloud into images, followed by the application of a line segment detector to extract 2D line segments; (2) back projection of these 2D line segments to the original coordinate system to obtain the final 3D line segments. However, these methods exhibit high sensitivity to noise and impose stringent requirements on image quality.

In this research thesis, the focus shifts away from direct line segment extraction on the original point cloud or strategies reliant on projection and back projection. Instead, a novel method is proposed, leveraging the inherent relationship between line segments and planes. The key methodology comprises three phases: firstly, preprocessing of the input point cloud involves subsampling and filtering. Secondly, a Principal Component Analysis (PCA)-based approach is introduced to extract local and global geometric features, elucidating the structural geometry of indoor point clouds, including doors, windows, beams, and pillars. Subsequently, extracted points are clustered to confer a definite shape upon the segments. Finally, an improved alpha-shape algorithm is employed to extract boundary points of structural elements within the room, culminating in the extraction of 3D line segment structures.

3. Objectives

The research objectives of this study are outlined as follows:

1. **Generate a 3D model for a detailed reconstruction of room structural geometry from LiDAR input.**

   The primary objective is to develop a methodology for creating a comprehensive 3D model that captures intricate details of room structural geometry utilizing LiDAR input. This involves leveraging the capabilities of LiDAR technology to produce detailed and accurate representations of indoor spaces.

2. **Formulate a technique to eliminate the need for converting 3D input data to 2D thereby avoiding loss of depth information in the reconstruction process.**

   The second objective aims to propose a technique that circumvents the common practice of converting 3D input data into 2D during the reconstruction process. By avoiding this conversion, the research seeks to retain and utilize the full-depth information inherent in the 3D data, thereby enhancing the precision of the reconstruction.

3. **Develop a methodology to determine the dimensions of the reconstructed structural elements of a 3D indoor model with a tolerance of less than 2mm, which is the industry standard**

   Another key objective is to devise a robust methodology for accurately determining the dimensions of the reconstructed structural elements within a 3D indoor model. The aim is to achieve a level of precision that adheres to industry standards, with a tolerance of less than 2mm. This precision is crucial for applications requiring accurate geometric representation.

4. **Devise a 3D modeling technique for indoor reconstruction with low computational complexity**

   The final objective involves the development of a 3D modeling technique tailored for indoor reconstruction that prioritizes low computational complexity. This aims to enhance the efficiency of the reconstruction process, ensuring that the proposed methodology is practical and resource-efficient for real-world applications.

By addressing these research objectives, the study aims to contribute to the advancement of 3D line segment extraction methodologies from unstructured point cloud data, particularly in the context of large-scale building environments.

4. Literature Review

This chapter serves as a comprehensive exploration of existing research, methodologies, and advancements relevant to the refinement of line frame constructions within interior room environments using 3D point cloud data. By critically analyzing prior work in this field, this chapter aims to establish a solid foundation for the proposed methodology, highlighting gaps in current knowledge, and providing a contextual framework for the study's innovative contributions to this domain.

4.1 Data Acquisition

Data capture is essential in the process of interior 3D reconstruction. Photogrammetry is a method that entails collecting images of an object or scene from various perspectives and utilizing those images to construct a three-dimensional representation. LiDAR, in contrast, employs the transmission of laser pulses towards a given environment and the subsequent measurement of the duration it takes for the pulses to reflect back, thereby generating a three-dimensional dataset in the form of a point cloud. Utilizing LiDAR point clouds as input for 3D reconstruction of indoor scenes offers numerous benefits [14-15]. The advantages encompass the capacity to acquire exceedingly precise and intricate spatial data, the ability to penetrate obstructed or congested surroundings, and the capability to gather data instantaneously. As a result of these benefits, LiDAR point cloud data has become more and more prevalent in 3D reconstruction approaches.

4.2 Line Frame Generation

The extraction of line segments in three-dimensional space is a well-established and ongoing subject of research. Over the past few decades, researchers from various disciplines have devised multiple approaches, with the most significant ones falling into four main categories: multi-view image-based, plane feature-based, point feature-based, and deep learning-based methods.

4.2.1 Multi-view image-based methods

Using mathematical reasoning and other techniques, multi-view stereo reconstructs the scene by obtaining several photos of the target object from various perspectives. Taylor et al. [16] used perspective projection to capture several images of a moving camera and reconstructed the 3D line segments of a target object. The recovery process is designed to minimize the overall squared distance between the measured segments and the projection of the rebuilt infinite lines, taking into account the structural and kinematic factors. Martinec et al. [17] extracted the 3D line segment structure from many views of images by breaking down a matrix that contains line correspondences. This scheme does not utilize point correspondence to enhance the reconstruction impact. The requirements specified by connection constraints and depth information were used to reconstruct 3D line segments representing the geometrical feature of 3D objects in the area to be detected, as shown in [18]. The method proposed by Lin et al. [19] involved extracting 3D line

segments by combining shaded pictures and point clouds. This approach was able to accurately extract line segments where planes intersected from a large number of raw scan points. Initially, acquiring 3D scanning equipment was both costly and challenging, leading to the frequent utilization of this approach to create 3D models. The multi-view image-based approaches are better suited for data obtained from a singular viewpoint. Nevertheless, it cannot analyze the data gathered from various sites. For instance, the indoor building point cloud obtained by the backpack-type 3D laser scanner exhibits a relatively intricate scene. If the images are projected in a multi-view manner, the line segment information will be obscured and intersect with each other, leading to the failure of these methods.

4.2.2 Plane Feature-based methods

The second category of methods employed to detect 3D line segments in point clouds relies on plane characteristics. The plane structure is frequently accompanied with the three-dimensional line segment structure. Hence, it is a viable approach to initially extract the plane structure and thereafter conduct line segment extraction based on this foundation. In [20], 3D line segments were discovered using a different approach compared to standard approaches. Instead of extracting contour points first and then linking them to fit 3D line segments, this method relied on point cloud segmentation, 3D-2D projection, and 2D-3D re-projection. Lin et al. [21] introduced a novel processing method to recover line segments from a point cloud scenario of significant scale. The main objective was to efficiently divide the input point clouds into a set of facets. The concept of "number of false alarms" was specifically created in the context of 3D point clouds to eliminate false positive line segment detections. In their study, Sampath et al. [22] introduced a framework for reconstructing polyhedral building roofs using aerial laser point cloud scanning equipment. The process begins by extracting three-dimensional line segments that intersect at the roofs' intersection. These line segments are then utilized to reconstruct the polyhedral building roofs. The extraction of 3D line segments was achieved by intersecting planes in [23]. The proposed methodology accurately identified line structures in the given circumstances in order to correctly calculate the stiff transformation. A prevalent limitation of these approaches is the difficulty in ascertaining the ends of the extracted line segments. Furthermore, plane-based approaches are better suited for large planes and exhibit lower sensitivity towards tiny planes.

4.2.3 Point feature-based methods

Typically, point feature-based methods begin by identifying boundary or contour points, and subsequently employ fitting techniques, such as least squares, to extract line segments. Several types of features, including the Gauss Map [24], curvature variation [25], normal difference [26], and features based on eigenvalue decomposition [27], have been suggested for the detection of border or contour points. In [24], the initial step involved applying Gaussian graph clustering to an unorganized point cloud. This process helped to remove points that are unlikely to be part of

edges. In the second stage, a more accurate iterative selection of the remaining feature points was carried out. This selection aimed to enhance the reliability and robustness of the system, especially when dealing with obtuse and acute angles. The detection of sharp edge features was achieved in [25] by analyzing the eigenvalues of the covariance matrix, which was defined by the k-nearest neighbors of each point. The evaluation of the results was conducted both qualitatively and quantitatively, using various dihedral angles and established instances of unorganized point clouds. The introduction of a new multi-scale operator called the difference of normal (DoN) for unorganized 3D point clouds was documented in [26]. The normal of each point was computed at various scales, and only those with a greater disparity in normals were chosen as boundary points. Hackel et al. [27] utilized a binary classifier to predict the contour score of each individual point. This was achieved by extracting a set of features from the neighborhood of the point. The contour scores are used as the foundation for constructing an overcomplete graph of potential contours. Jarvis [28] enhanced the procedure for constructing the convex hull to include certain concavities within the resulting shape. Zhang et al. [29] introduced the 3D guided multi-conditional GAN (3D-GMcGAN) as a method to identify contour points in outdoor scene data that align with human visual perception. The suggested solution introduces a parametric framework in which a new similarity measurement is used to compare two parametric models. Furthermore, a structured learning framework is specifically created to facilitate the identification of the desired contour distribution through initial assistance. In their study, Chen and Yu [30] introduced an innovative approach for generating and smoothing feature lines. This approach involves two primary steps: first, extracting outline points based on vector distribution and clustering; second, sorting feature points based on their vector deflection angle and distance, and fitting them using an enhanced curve fitting method. The primary limitation of these approaches that rely on point features is the susceptibility of the feature point itself to noise interference.

4.2.4 Deep Learning based methods

Contemporary advances in fundamental science and advanced computer hardware and software have given rise to a multitude of deep-learning techniques that are being used across a wide range of industries. These developments have had a profound impact on conventional lifestyle and industrial practices. Deep learning has exhibited exceptional performance and attained significant accomplishments in the field of 2D image processing [31–33]. Nevertheless, the convolution procedures on unstructured point cloud data remain challenging due to the presence of high redundancy, uneven density distribution, nonlinear error, and a substantial volume of data. Hackel et al. [27] introduced a method for extracting contour points in a point cloud using a learning-based approach. In this method, a classifier is used to forecast each individual point. Next, the most suitable set of contour points is determined by solving high-order Markov Random Fields (MRFs). PointNet [34] introduced a deep learning framework that operates directly on unstructured point clouds. PointNet++ [35] expanded upon PointNet by implementing it hierarchically in local regions for computing, leading to the development of numerous cutting-edge methods [36]. Yu et al. [37] introduced a novel approach for extracting contour points using deep learning theory, drawing inspiration from recent advancements in point cloud learning networks. The proposed

framework was specifically built to manipulate points that are clustered together in local patch sets, and it was trained to learn and consolidate these points. Zhang et al. [29] introduced the 3D guided multi-conditional GAN (3D-GMcGAN) as a method to identify contour points in outdoor scene data that align with human visual perception. The approach for linear structure extraction based on deep learning can only extract contour lines that are consistent with the marked samples, due to the restricted number of samples used. Nevertheless, real-life environments are highly intricate, and the available number of manually annotated examples is insufficient to identify a wide range of contour or edge points accurately.

As previously mentioned, the disadvantage of point feature-based approaches is their susceptibility to noise, resulting in the omission or misidentification of extracted feature points. The efficacy of the multi-view image-based method is significantly influenced by the quality of the photos, making it more appropriate for point cloud data obtained from a single view angle in a straightforward scene. One drawback of plane-based approaches is that they are better suited for processing larger planes but less efficient for smaller planes. Deep learning algorithms heavily rely on annotated data. Given that this study focuses mostly on extracting information about 3D line segments in interior environments, it is logical to utilize the point-based method.

The point-based method proposed in this research leverages geometric features extracted from Principal Component Analysis (PCA) on both a global and local neighborhood level, coupled with Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering. Global PCA captures the general trends and structural components in the point cloud data collection. Principal components, which correlate to the major axes of the point distribution, reveal the room's structural arrangement and direction. It gives a complete picture of the room's structural geometry by analyzing the spatial arrangement of components like pillars and beams. PCA extracts characteristics from clustered point cloud areas at the neighborhood level. Localized analysis is essential for capturing structural element details and changes. DBSCAN clustering refines the identification of point clusters that may represent corners or edges. PCA and DBSCAN improve the method's capacity to distinguish delicate room details, enabling more nuanced structural geometry extraction. When combined with the clustering methodology, PCA's versatility in capturing both global and local features makes it a strong option for gathering data regarding corners, edges, beams, and pillars in interior spaces. Furthermore, this methodology proves its effectiveness in dealing with various and complex room architectures, thereby overcoming the restrictions of alternative methods. As a result, it makes a significant addition to the field of 3D reconstruction and geometric feature extraction.

To summarize, this research has made noteworthy contributions to the field, which can be outlined as follows:

1. Presenting a method for extracting 3D line segments from indoor room point clouds, which is specifically designed to be simple in concept and easy to apply. This technique solely relies on the original point cloud, obviating the necessity for additional information such as images or reconstructed models.

2. Applying several constraints to the algorithm to efficiently remove unnecessary information. With this function, 3D line segment misidentifications are significantly decreased and comprehensive information restoration accuracy is improved.

3. Directly addressing the challenge of 3D structural line detection without resorting to the conversion of the problem into 2D space. By preserving and exploiting the complete depth information inherent in 3D data, this method significantly elevates the precision of the reconstruction process.

4. Validating the effectiveness of the proposed methodology in successfully managing various and complex room structures, confirming its adaptability and resilience in practical situations.

5. Proposed Work

To address the shortcomings identified in the existing literature, a novel technique for extracting 3D line segments is introduced. This method is characterized by its straightforward conceptual framework and its ease of implementation. The proposed approach comprises three distinct stages: data pre-processing, Contour point extraction, and 3D line framework refinement, as illustrated in Figure 2.

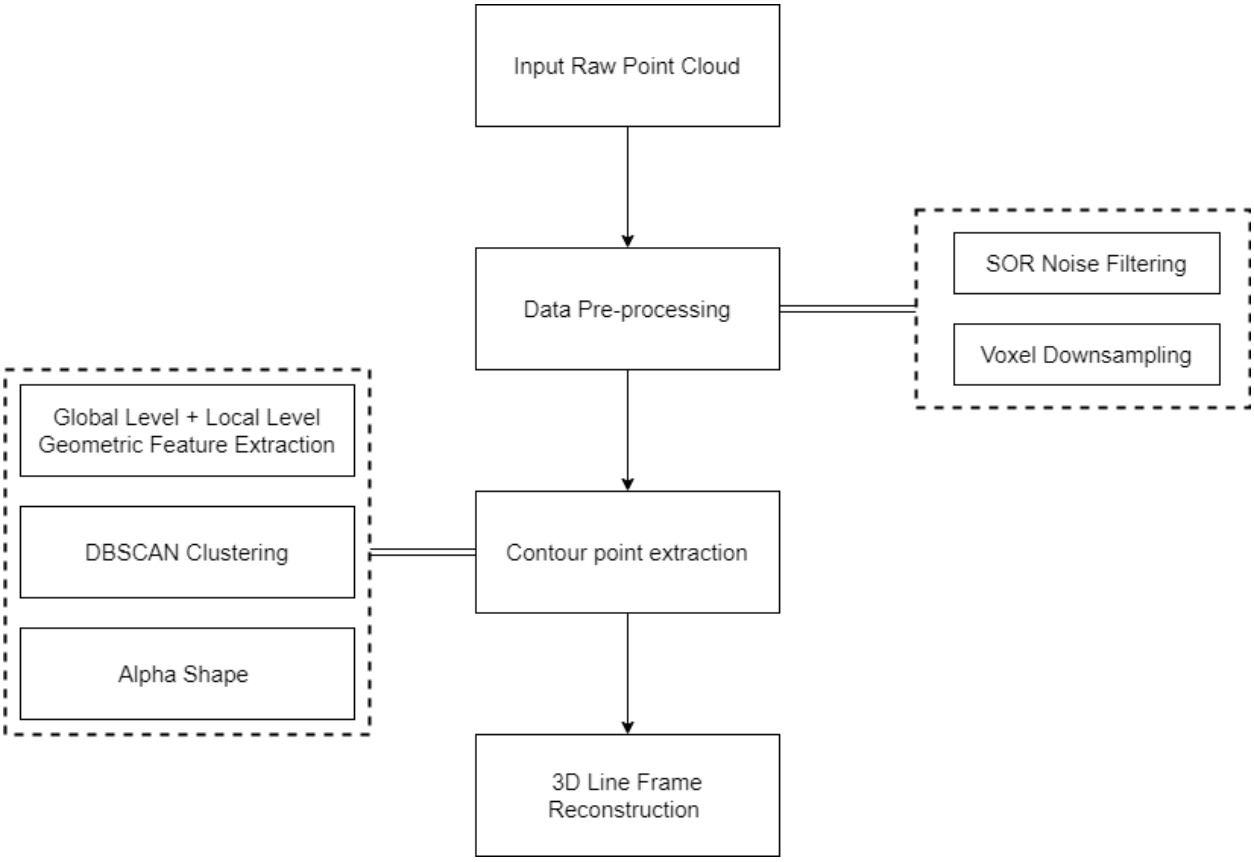

Figure 1. Overall flow of the proposed 3D line frame extraction method

For the large-scale point clouds, which are acquired by the current variety of LiDAR systems, they also bring a great challenge in data processing. To improve operational efficiency, appropriate data filtering and subsampling are necessary. Pre-processing of the data, which includes noise filtering and subsampling, is done in the first step, given the input point cloud. The second phase primarily consists of three steps: Geometric Feature Extraction at both the Global and Local level using Principal Component Analysis (PCA), density-based clustering, and finally, the alpha shape technique is utilized to extract the boundary line segments.

5.1 Point cloud dataset

Using technologies like laser scanning and photogrammetry, point cloud data provides a precise three-dimensional depiction of interior spaces, making it indispensable in the fields of civil engineering and interior design. Although photogrammetric approaches provide significant value, they also include certain limitations. These factors encompass sensitivity to environmental circumstances, such as variations in lighting and shadows, which have the potential to undermine the accuracy of the data. Photogrammetry's dependence on image-based data renders it vulnerable to occlusions, which may lead to point clouds that are either incomplete or distorted. Furthermore, the technique can be laborious and resource-intensive, particularly in intricate indoor settings, because it requires numerous photos and involves substantial computational processing. Moreover, the task of capturing intricate details or complex geometries may provide difficulties. On the other hand, LIght Detection And Ranging (LiDAR), a technique used to gather point cloud data, is notable for its effectiveness in precisely and quickly capturing intricate spatial data. LiDAR is less susceptible to weather conditions, providing benefits over photogrammetry in terms of velocity, accuracy, and the capacity to record intricate features, rendering it a favored option for professionals in civil engineering and interior design applications.

To evaluate the efficacy of the suggested methodology, experiments were conducted utilizing point cloud data, a dataset of colored point clouds with high spatial resolution, which represents interior situations well. The input dataset for this study comprises a colored point cloud captured using a NavVis Laser scanner [38]. This point cloud represents an entire floor of a building and is stored in the. LAS format. With a total of 4,244,416 points, this dataset provides a detailed and comprehensive representation of the entire floor, including multiple rooms with varying interior geometries. These rooms may differ in size, shape, and layout, making the dataset particularly valuable for various analyses and applications within the study.

The methodology's capabilities and restrictions are better assessed using colored point clouds in real-world circumstances. In the context of the NavVis dataset, we have developed three distinct use case scenarios, designated Cases A, B, and C, with the primary goal of evaluating and validating the methodology employed by our algorithm, as shown in Figure 3. The no of points present in each point cloud scenario is detailed in Table 1. These cases serve as representative testbeds for evaluating the algorithm's efficacy and dependability in various architectural settings. Case A displays a point cloud depicting a wall with two distinct doorways. The presence of numerous doorways within a single structural element poses a challenge to the algorithm's ability to precisely capture and analyze architectural features. In Case B, the point cloud represents a wall configuration characterized by the presence of three windows. The varying window sizes and positions introduce complexities that enable us to evaluate the algorithm's ability to accurately distinguish and delineate architectural components. Case C presents us with a wall containing two distinct doors, with beams serving as architectural elements separating them. This scenario tests the algorithm's ability to recognize and differentiate structural elements despite the spatial

complexities introduced by beams. The analysis of these three use cases not only demonstrates the adaptability of our proposed methodology but also offers valuable insights into its applicability in a variety of architectural contexts.

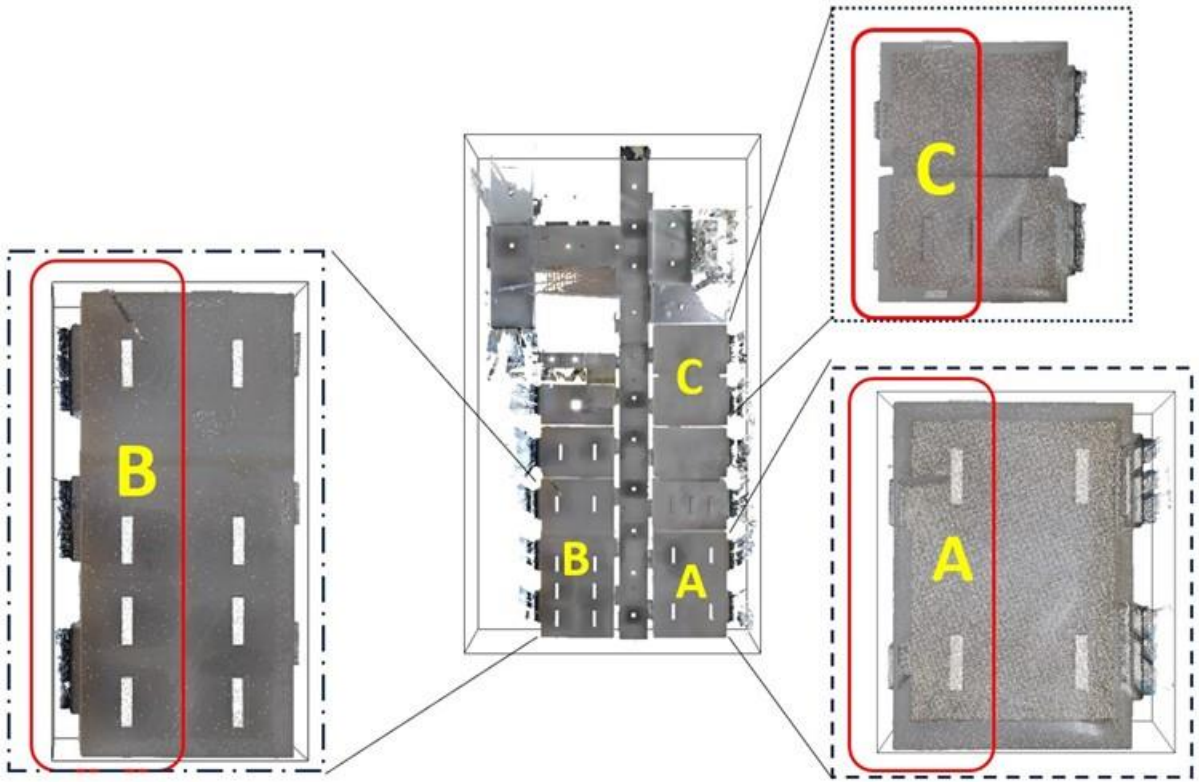

Figure 2. NavVis Dataset - Three Distinctive Architectural Cases (A, B, and C)

Delineating the number of points captured in various scenarios, Table 1 provides information on the NavVis Scanner indoor dataset. For Case A, the dataset consists of 224,423 data points, which depict a room with a wall that has one door open and another door closed. Case B consists of 297,172 data points, which represent a room with a wall that has three windows and a beam running across them. Case C consists of 193,267 points, depicting a room with a wall that has both an open door and a closed door. There is a pillar that acts as a divider between the two doors. This dataset provides a comprehensive depiction of indoor spaces, enabling the examination and reconstruction of many architectural contexts.

Table 1. Indoor scenarios used as the use case for the proposed methodology

Dataset	**No of points**	**Scenario**	**No of points**	**Description**
NavVis Scanner indoor dataset	4 244 416	Case A	224 423	Room wall with one open and one closed door
		Case B	297 172	Room wall with three windows and a beam across them.
		Case C	193 267	Room wall with one open door and one closed door with a pillar separating the doors.

5.2 Data Preprocessing

In this section, the pre-processing stage of the proposed methodology is elaborated, including two essential sub-steps for improving the quality of point cloud data. Initial denoising exploiting the Statistical Outlier Removal (SOR) algorithm is utilized to enhance the precision and dependability of subsequent analyses by reducing noise and outliers.

Within the pre-processing stage of the proposed methodology, the Statistical Outlier Removal (SOR) algorithm assumes a pivotal role in enhancing the quality of point cloud data. The SOR algorithm systematically examines each point in the dataset, evaluating its statistical deviation from the overall distribution. Points identified as outliers, falling beyond predetermined statistical thresholds, undergo removal. This meticulous process effectively eradicates noise and extraneous data points, thereby augmenting the precision and reliability of the point cloud. By mitigating outliers, SOR ensures subsequent analyses are conducted on a more accurate and representative dataset, thereby elevating the overall quality of the results. Noteworthy parameters in the SOR algorithm, namely the *number of neighbors* and *standard deviation*, significantly influence the filtering process. The *number of neighbors* parameter delineates the size of the local neighborhood considered during the algorithm's evaluation of statistical properties. A heightened number of neighbors enhances the algorithm's resilience to variations in point density, facilitating a more comprehensive assessment of local point cloud characteristics. Conversely, the *standard deviation* parameter establishes the threshold for identifying outliers based on their statistical deviation from the mean of the local neighborhood. A reduced standard deviation permits a more stringent filtering process, adept at detecting and removing points with subtle deviations from the norm. Conversely, a larger standard deviation threshold allows for a more lenient filtering, retaining points with a broader range of statistical variations. The meticulous adjustment of these parameters is imperative for achieving an optimal equilibrium between noise elimination and the preservation of pertinent data, exerting direct influence on the algorithm's sensitivity to outliers and the overall quality of the denoised point cloud.

The Statistical Outlier Removal (SOR) algorithm is subjected to testing on Case A, and the outcomes are illustrated in Figure 4. In this evaluation, parameters such as a *standard deviation* of 1 and a *number of neighbors* set to 6 were applied, resulting in the filtered point cloud depicted in Fig 4(b), which contains 207,388 points. This particular configuration demonstrates an effective reduction of noise and outliers while preserving a significant portion of the original dataset. Notably, the judicious selection of parameters in Fig 4(b) strikes a balance between noise reduction and data preservation, exemplifying the nuanced optimization of SOR for enhanced point cloud quality and subsequent analytical precision.

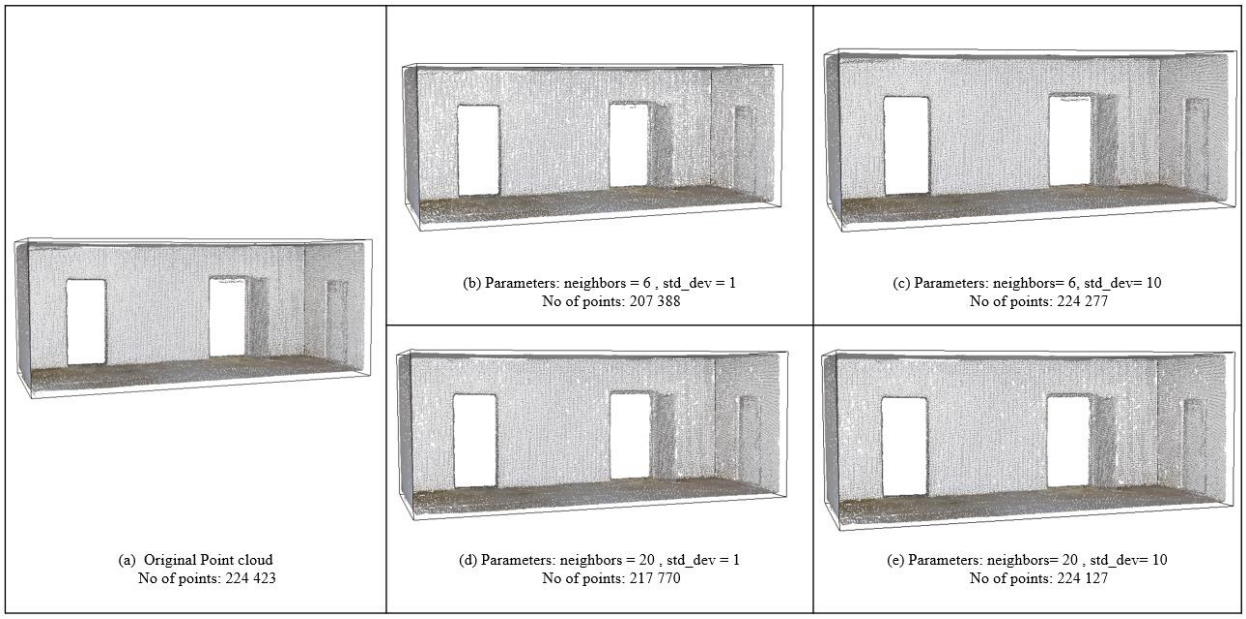
(a) Original Point cloud
No of points: 224 423
(b) Parameters: neighbors = 6 , std_dev = 1
No of points: 207 388
(c) Parameters: neighbors= 6, std_dev= 10
No of points: 224 277
(d) Parameters: neighbors = 20 , std_dev = 1
No of points: 217 770
(e) Parameters: neighbors= 20 , std_dev= 10
No of points: 224 127

Figure 3. Application of SOR filter on Case A

Following the application of the Statistical Outlier Removal (SOR) filter, down-sampling is the next step in the process. There are numerous down-sampling techniques to choose from, but voxel down sampling is especially notable for its effectiveness in reconstructing line frames of indoor structural elements. Voxel down sampling is the process of partitioning the point cloud into three-dimensional voxel grids and selecting a representative point from each voxel. The approach is beneficial for reconstructing indoor structural elements, such as line frames, because it may effectively decrease data density while maintaining important geometric elements. Voxel down sampling achieves an equilibrium between preserving structural features and enhancing computing efficiency, making it ideal for applications that require precise representation of indoor structural aspects. Alternative down-sampling techniques include random sampling and uniform sampling. However, voxel down sampling is favored for conditions that require a balanced combination of data reduction and preservation of structural complexities. Case A was subjected to voxel downsampling; the results are shown in Figure 5, and Table 2 presents the quantified findings. For the purposes of this investigation, three different voxel sizes were tested: 0.1, 0.05, and 0.03 in Figure 5(a), Figure 5(b), and Figure 5(c). The selected voxel size of 0.05 exhibits two main benefits. Initially, it yields a point cloud consisting 47,815 points, effectively achieving a harmonious equilibrium between data reduction and the retention of structural intricacies. Furthermore, the computational time for this specific configuration is remarkably efficient, taking only 0.032 seconds. This demonstrates an optimal processing speed, which strongly supports the choice of a voxel size of 0.05. This voxel size achieves a balanced compromise between data density and computational efficiency in the voxel down sampling process for Case A.

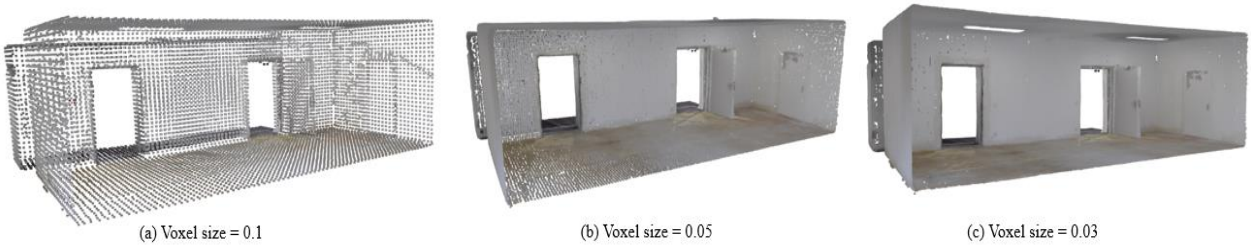

Figure 4. Voxel Down Sampling on noise-filtered Case A

The utilization of Statistical Outlier Removal (SOR) filtering in conjunction with voxel down sampling is identified as a vital preliminary procedure, greatly boosting the effectiveness of contour edge point extraction. SOR filtering effectively mitigates the presence of noise and outliers in the point cloud, resulting in a more precise and dependable depiction of the underlying structural components. Then, voxel down sampling maximizes the data density of the point cloud by striking a balance between computing efficiency and the preservation of important geometric elements. In addition to fine-tuning the point cloud, this thorough pre-processing establishes a strong basis for the contour edge point extraction. SOR filtering and voxel down sampling work together to improve the accuracy and efficiency of extracting contour edge points. This is important for various applications such as 3D reconstruction, modeling, and spatial analysis, as it helps to remove unnecessary data and reduce computing workload.

Table 2. Quantified Results of Voxel Down Sampling in Case A with Varying Voxel Sizes

Voxel size:	0.1	**0.05**	0.03
No of points:	12336	**47815**	124119
Time:	0.022 sec	**0.032 sec**	0.077 sec

5.3 Contour extraction

The calculation of normals is performed before the computation of PCA-based geometric features in the down-sampled point cloud. Before generating PCA-based geometric features, computing normals in the down-sampled point cloud is a strategic way to guarantee meaningful and accurate feature extraction. The orientation of surfaces at each point is disclosed by normals, which offer an essential basis for further geometric analysis. The intrinsic structural properties are more accurately represented and aligned by identifying normals in the down-sampled cloud, which improves the accuracy and dependability of the PCA-based geometric feature extraction procedure.

Principal Component Analysis (PCA) based geometric feature extraction is a powerful technique employed in point cloud analysis to discern and quantify essential geometric characteristics. In this process, PCA is applied to local neighborhoods within the point cloud, determining the principal axes and their associated variances. By analyzing the covariance matrix of points within a local region, PCA identifies the directions of maximum and minimum variance, revealing

intrinsic geometric features of the underlying surfaces. In Principal Component Analysis (PCA), the eigenvalues are typically arranged in descending order. Therefore, the first eigenvalue is the largest, representing the direction of maximum variance in the dataset, while the last eigenvalue is the smallest, indicating the direction of minimum variance. Extracted geometric features derived from the eigenvalues [27] obtained through Principal Component Analysis (PCA) are presented in Table 3.

Table 3. Geometric Features Extracted from PCA-Based Eigenvalues

Descriptor	Definition
Eigen Values	$d_v^g = \lambda_v$ with $v \varepsilon 1, 2, 3$
Sum of Eigen Values	$d_4^g = \sum_1^v \lambda_v$
Linearity	$d_5^g = (\lambda_1 - \lambda_2)/\lambda_1$
Planarity	$d_6^g = (\lambda_2 - \lambda_3)/\lambda_1$
Sphericity	$d_7^g = \lambda_3/\lambda_1$
Anisotropy	$d_8^g = (\lambda_1 - \lambda_3)/\lambda_1$
Omnivariance	$d_9^g = \sqrt[3]{(\lambda_1.\lambda_2.\lambda_3)}$
Eigentropy	$d_{10}^g = -\sum \lambda_v . \ln(\lambda_v)$
Parallelity_x	$d_{11}^g = 1 - \lvert u_x.e_3 \rvert$
Parallelity_y	$d_{12}^g = 1 - \lvert u_y.e_3 \rvert$
Parallelity_z	$d_{13}^g = 1 - \lvert u_z.e_3 \rvert$

The geometric features derived from PCA-based eigenvalues provide valuable insights into the characteristics of the underlying point cloud geometry. The sum of eigenvalues gives a comprehensive measure of overall variability in the dataset. Omnivariance characterizes how uniformly variances are distributed along different axes within a local neighborhood, offering an understanding of isotropy. Eigentropy reflects the complexity associated with the eigenvalues, capturing the information content. Anisotropy quantifies the degree of shape deviation from isotropy, while Planarity and Linearity emphasize the proportion of geometry lying within a local plane and the shape's elongation, respectively. Surface Variation provides insights into surface variations, with a focus on the smallest eigenvalue. Lastly, Sphericity quantifies the degree of deviation from a perfect sphere, indicating the sphericity of the shape. These features collectively offer a nuanced understanding of the structural characteristics embedded in the point cloud.

On a global scale, it was observed that the same PCA-based geometric features did not yield consistent results across different cases, namely Case A, Case B, and Case C. This discrepancy underscored the importance of local neighborhood analysis for a more nuanced understanding of the structural geometry. Recognizing this need, PCA analysis was further employed at the local level, specifically focusing on the neighborhood details using a KD Tree. This refined approach aimed to capture local intricacies and variations, providing a more context-specific comprehension of the geometric features within each distinct case.

At the local neighborhood level, an empirical observation revealed that two specific geometric features, namely surface curvature and anisotropy, exhibited discernible significance in the

detection of edge and corner points. Notably, edge points and corner points tended to manifest higher surface curvature values in contrast to points situated on flat surfaces. This characteristic was attributed to the diverse orientations and reduced variation within their respective local neighborhoods. Moreover, edge points and corner points consistently demonstrated lower anisotropy values due to their typical location at the boundaries between distinct surfaces, each possessing disparate orientations. As a result, a refined approach was devised, leveraging the insights gained from these findings. Anisotropy values below the threshold, where the threshold is defined as the mean, were exclusively chosen for further analysis. Similarly, for curvature, solely values exceeding the threshold, where the threshold is determined as the mean of curvature results, were considered in subsequent evaluations. This methodological choice was grounded in the premise that such thresholds effectively discriminated edge points based on the characteristic anisotropy and curvature patterns identified within the local neighborhoods. After the detection of edge points, the algorithm proceeds to utilize the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) technique for the purpose of clustering the discovered edge points [39-40]. The DBSCAN algorithm is utilized to aggregate adjacent edge points into clusters, taking into account a predefined distance threshold. The choice of an epsilon value in the DBSCAN algorithm is determined through a thoughtful analysis of the desired spatial resolution and the density of edge points in the specific context. The objective is to accurately identify significant clusters while minimizing the impact of noise and appropriately grouping edge points. The clusters that are obtained from the edge framework, which serves to accurately define the structural edges of the indoor scene environment.

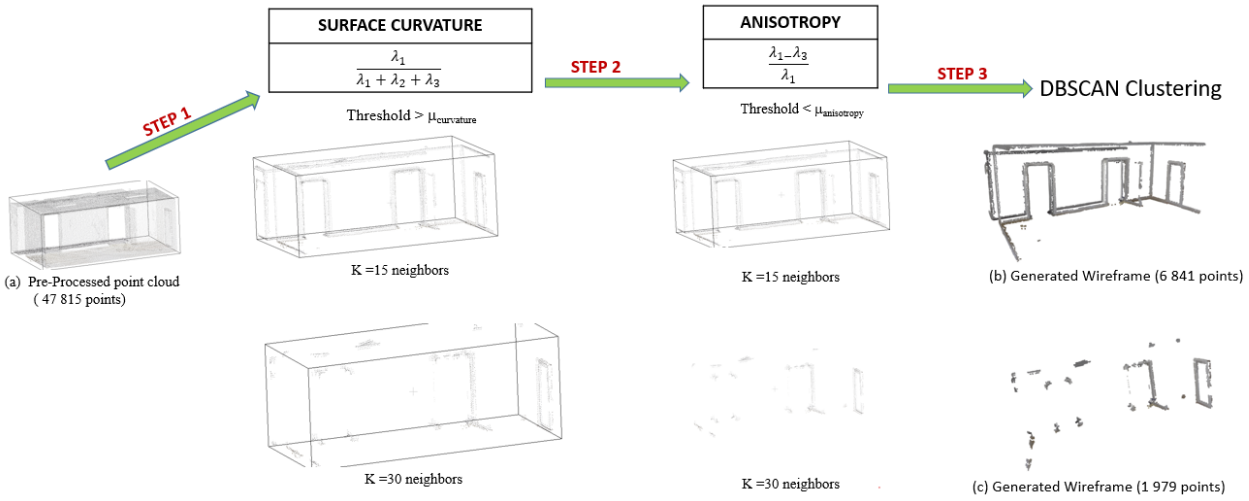

Figure 5. Results of Edge Detection with Varying Neighborhoods on Case A

In the course of experimentation, it became evident that the selection of the local neighborhood size significantly influences the outcomes of edge detection. Specifically, when employing a larger neighborhood size of 30 neighbors, the extracted corner points were notably sparse compared to the results obtained with a smaller neighborhood of size 15. This finding suggests that a smaller local neighborhood is more adept at capturing fine structural geometry details within the indoor

scene dataset. Visual results illustrating this observation are encapsulated in Figure 6. The contour representation highlights the efficacy of using a more constrained neighborhood size, emphasizing the importance of parameter tuning for optimal feature extraction in point cloud analysis.

For improved efficiency of the precise depiction of structural geometry, Alpha Shape is generated from the extracted wireframe. The Rolling Ball Pivoting Algorithm (RBP) is a widely used method for generating the Alpha Shape from an extracted wireframe, enhancing the efficiency of precise structural geometry depiction [41-42]. RBP operates by iteratively pivoting a ball over the point cloud. In each iteration, the ball "rolls" along the edges of the wireframe, collecting points that contribute to the Alpha Shape. The algorithm pivots at each vertex of the wireframe, extending the ball's radius until it encounters the next vertex. The significance of epsilon values in RBP lies in determining the threshold for point inclusion. A higher epsilon value, such as 5, would result in a more permissive inclusion criterion, incorporating a larger set of points and potentially generating a coarser Alpha Shape. Conversely, a lower epsilon value, like 0.8, imposes a more stringent condition, leading to the inclusion of a more selective subset of points and yielding a finer Alpha Shape with increased precision.

Figure 6. Stage-wise results of Proposed Methodology

The comprehensive results of the methodology across three distinct cases (A, B, and C) are illustrated in Figure 7. Each row corresponds to a specific case, depicting the 3D point cloud obtained after the stages of pre-processing, edge detection, and edge framework application,

showcasing the effectiveness of the methodology in extracting and refining structural features in indoor scenes.

Case A is a wall with two door openings as shown in Figure 7. The algorithm demonstrates its efficacy in accurately representing the structural limits of the space, including the door openings. Nevertheless, it is apparent that the detection of the door frame was not fully comprehensive. The aforementioned constraint might be ascribed to the comparatively diminished quantity of data points that depict the door frame inside the input point cloud. The limited availability of data points pertaining to the door frame poses a challenge for the algorithm in accurately discerning and reconstructing the entirety of the door frame structure. Resolving this matter necessitates the implementation of approaches aimed at improving the process of acquiring point cloud data.

The present study also assessed the efficacy of the proposed methodology through the examination of Case B, which serves as a representative subset of an interior room scene featuring three windows. The wireframe successfully depicted the structural elements of the room, such as the windows, thus indicating the efficacy of the proposed methodology in precisely representing the room's structural characteristics but the representation of the beam between the windows and floor remained incomplete as depicted in Figure 7.

Within the dataset, Case C presents a complex scenario characterized by the presence of a wall with two distinct doors that are divided by a central pillar. Notwithstanding the intricacy of this arrangement, our proposed approach exhibited exceptional abilities in reconstructing the structural geometry of the space. The depiction successfully encompasses the fundamental components of the scenario, encompassing both the doors and the pillar. Nevertheless, it is important to acknowledge that although our methodology demonstrated exceptional proficiency in reconstructing the intended structural characteristics, it also inadvertently restored several undesired components. The aforementioned discoveries provide essential perspectives for the continued improvement and enhancement of our methodology, guaranteeing its resilience and precision in complex situations. Case C serves as a demonstration of the efficacy of our methodology in addressing intricate real-world problems, hence facilitating advancements in spatial reconstruction techniques across diverse applications.

Table 4. Quantitative Analysis of Processing Time and Point Cloud Metrics across Methodology stages

Dataset		Data Pre-processing		Edge Detection			Edge Refinement		
Scene	No of Points	Processing Time (sec)	No of points	Epsilon Value	Processing Time (sec)	No of points	Alpha radius	Processing Time (sec)	No of points
Case A	224,423	0.08	90,652	0.06	63.44	21,794	0.8	177.55	18,238
Case B	297,172	0.11	123,556	0.05	80.77	20,622	0.8	356.29	18,837
Case C	193,267	0.11	77,659	0.06	45.20	11,204	0.8	93.24	10,482

In our comprehensive evaluation of the proposed methodology, we present a detailed breakdown of processing time and the number of points in the point cloud at various key stages of the reconstruction process. This analysis, summarized in Table 4, provides valuable insights into the efficiency and performance of our approach.

5.4 Evaluation metrics

The evaluation procedure generated the following key performance indicators:

True Positives (TP): The number of correctly identified and matched structural elements as line segments in the reconstructed framework.

False Positives (FP): The number of line segments in the reconstructed framework that are not supported by structural elements in the point cloud data.

False Negatives (FN): The number of structural elements in the point cloud data that are not correctly designated as line segments in the reconstructed framework.

Table 5. Evaluation Metrics for the proposed methodology

Evaluation Metric	***Significance***	***Case A***	***Case B***	***Case C***
$Precision = \frac{TP}{TP + FP}$	The proportion of correctly identified structural elements among all elements predicted	0.85	0.875	**0.964**
$Recall = \frac{TP}{TP + FN}$	Proportion of correctly identified structural elements among all actual elements.	0.78	0.87	**0.93**
$F1\ Score = \frac{2 \times (Precision \times Recall)}{Precision + Recall}$	balances the trade-off between precision and recall, offering a consolidated measure of the methodology's effectiveness.	0.814	0.872	**0.946**
$IoU = \frac{TP}{TP + FP + FN}$	measures the overlap between predicted and actual positive instances.	0.69	0.729	**0.9**
$ER = \frac{FP + FN}{TP + FP + TN + FN}$	measures overall classification accuracy	0.23	0.212	**0.081**

For each case, the evaluation metrics Precision, Recall, F1 score, Intersection over Union (*IoU*) and Error Rate (*ER*) were calculated using True Positives (*TP*), False Positives (*FP*), and False Negatives (*FN*), as shown in Table 5.

The study introduces an innovative approach for refining line frame constructions within interior room environments using 3D point cloud data directly. Evaluating the methodology across distinct cases demonstrates its effectiveness in handling diverse structural complexities as shown in Table 5. In Case A, representing a single wall with a door opening, the algorithm achieved a commendable balance between Precision (0.85) and Recall (0.782), resulting in an F1 score of

0.814 and IoU of 0.69. Moving to Case B, a more intricate indoor scene featuring three windows and a beam, the algorithm yielded a higher Precision of 0.875. However, with a Recall of 0.87, it still maintained a robust F1 score of 0.872 and IoU of 0.729. Case C, depicting a single wall with two doors and a pillar, showcased exceptional performance, boasting a Precision of 0.964 and a Recall of 0.93. This outstanding performance translated into an impressive IoU score of 0.9 and a minimal Error Rate of 0.081. These results underscore the methodology's adaptability to varying structural geometries, with Case C particularly standing out as promising for reconstructing complex indoor scenes. The findings collectively highlight the efficiency and versatility of the proposed algorithm across different datasets and scenarios.

Table 6. Comparative Analysis with existing literature

Method	**IoU**	**ER**
Region Growing	0.6364	0.3636
RANSAC	0.0455	0.9545
Nearest-KNN	0.4545	0.5455
DoN	0.3182	0.6818
Voxel Clustering	**0.8182**	**0.1818**
Proposed Method (Case A)	0.69	0.23
Proposed Method (Case B)	0.729	0.212
Proposed Method (Case C)	**0.9**	**0.081**

The study's comparative analysis against existing unsupervised methods revealed highly promising outcomes as shown in Table 6. The evaluation extended across three datasets: Case A, Case B, and Case C. Case A demonstrated a notable IoU of 0.69 but with a higher ER of 0.23. Similarly, Case B exhibited a competitive IoU of 0.729, accompanied by an ER of 0.212. Particularly, in Case C, where two doors were separated by a pillar, the proposed methodology showcased superior performance with an IoU (Intersection over Union) of 0.9 and a remarkably low Error Rate (ER) of 0.081. This outperformed the Voxel Clustering method, which yielded an IoU of 0.8182 and an ER of 0.1818. The results affirm the efficacy of the proposed methodology, especially in Case C, where it excels in capturing complex indoor scenes with distinct structural elements. However, the study also acknowledges limitations, such as higher error rates in Cases A and B, suggesting potential areas for further refinement or exploration. These findings underscore the methodology's strengths while providing valuable insights for future enhancements.

6. Conclusion

Using 3D point cloud data directly, the study introduces a novel technique for the refinement of line frame constructions within interior room environments. Three distinct datasets, denoted as Cases A, B, and C, were used to conduct a comprehensive evaluation of the proposed methodology. These datasets were carefully chosen to represent a variety of indoor room scenarios with differing degrees of complexity.

- Working directly on 3D point cloud data is more effective than converting it into 2D, computing edges, and then back into 3D space, as the direct approach preserves the inherent spatial information and structural nuances present in the original 3D dataset. By avoiding intermediate transformations, the methodology can capture and retain the full three-dimensional context, providing a more accurate and detailed representation of the interior room environments. This streamlined process ensures that the refined line frame constructions maintain their integrity and precision without the potential loss of information associated with multiple conversions between 2D and 3D representations.
- The application of Statistical Outlier Removal (SOR) and voxel downsampling with a size of 0.05 as pre-processing steps before PCA-based contour detection ensures a cleaner and more refined point cloud dataset, enhancing the accuracy and effectiveness of the subsequent contour detection algorithm by reducing noise and irrelevant data points.
- In PCA-based geometric feature extraction, a smaller neighborhood is preferred because it allows for a more localized analysis of the point cloud data. Using a small neighborhood, such as 10 neighbors, ensures that the algorithm focuses on the immediate vicinity of each point, capturing finer details and variations in the local geometry. This approach is particularly beneficial when dealing with intricate structural elements, as it enhances sensitivity to local changes and contributes to a more accurate representation of the geometric features within the dataset.
- By combining the Alpha Shape and Rolling Ball Pivoting techniques, the methodology produced enhanced line frame models capable of accurately depicting convex and concave interior features. Importantly, the proposed method excelled at accurately representing interior room environments' structural boundaries, door apertures, and windows.
- The methodology outperforms existing unsupervised methods, showcasing a superior IoU of 0.9 and an impressively low Error Rate (ER) of 0.081 compared to the Voxel Clustering method, especially in Case C. However, while excelling in capturing complex scenes, the study acknowledges limitations, such as higher error rates in Cases A and B, suggesting areas for potential refinement. The overall findings underscore the efficiency and adaptability of the proposed algorithm, providing valuable insights for future enhancements and applications in diverse scenarios.

7. Future Scope

A crucial future scope for improvement lies in optimizing data acquisition methods to ensure the accurate capture of intrinsic details in structural geometry. Enhancing the precision of data collection, whether through advancements in laser scanning or photogrammetric techniques, is essential for obtaining a more comprehensive and detailed representation of indoor environments. Improvements in data acquisition will directly impact the quality of the point cloud data, enabling the proposed methodology to better discern subtle structural features. This enhancement can contribute to further refining the algorithm's performance, particularly in scenarios where intricate details play a significant role.

Another potential direction involves enhancing the algorithm's performance in scenarios with slightly higher error rates, as observed in Cases A and B. This may involve investigating and implementing additional features or refining existing parameters to improve accuracy.

Additionally, the methodology could be extended to handle dynamic environments, accommodating scenarios where structural elements may change over time. Moreover, considering the rapid evolution of sensor technologies, exploring compatibility with emerging hardware and data sources may further enhance the methodology's capabilities.

8. Publications

Journals:

1. S. Kurup and A. Bhise, "Automated Extraction of Indoor Structural Information from 3D Point Clouds," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 4s, pp. 723-730, 2024.
2. S. Kurup and A. Bhise, "Refining Line Frame Construction from 3D Point Clouds: DBSCAN and Alpha Shape Approach," *International Journal of Engineering Trends and Technology* (Accepted yet to publish).

Conference:

1. S. Kurup and A. Bhise, "A Systematic Review of Automated Reconstruction of Indoor Scenes Using Point Clouds," in *2021 International Conference on Image, Video Processing, and Artificial Intelligence (IVPAI)*, November 2021, vol. 12076, pp. 151-156, SPIE.

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